Project eems048
Mobility Decision Science pillar

U.S. DEPARTMENT OF ENERGY
SMARTMOBILITY
Systems and Modeling for Accelerated Research in Transportation

The Spatial Distribution and Impacts of One-Way Carsharing

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2019 Vehicle Technologies Office Annual Merit Review
June 11, 2019

Argonne NATIONAL LABORATORY · INL Idaho National Laboratory · BERKELEY LAB · OAK RIDGE National Laboratory · NREL NATIONAL RENEWABLE ENERGY LABORATORY

OVERVIEW

Timeline

- Start date: Oct 2016
- End date: Sep 2019
- INL: 100% complete
- LBNL: 75% complete

Budget

- Total funding
  - $150k INL
  - $225k LBNL
- Funding
  - FY17: LBNL $75k, INL $150k
  - FY18: LBNL $75k
  - FY19: LBNL $75k

Barriers

- Limited understanding of impacts of carsharing and transportation network company services on net energy use and relationship with transit

Partners

- UC Berkeley and Lawrence Berkeley National Laboratory (LBNL)
- Idaho National Laboratory (INL)
- car2go provided data under previous contract with DOT FHWA
- Other sources of data on 5 cities

PROJECT RELEVANCE: Why study one-way carsharing?

- Conduct early-stage R&D at the traveler level to better understand behavioral drivers of, and barriers to, increased mobility energy productivity of future integrated mobility systems
- Understand the energy implications from shifts in personal travel, including in public transit, to emerging transportation modes such as one-way carsharing
- Estimate the relationships between transit accessibility, urban form, and impacts from one-way carsharing
- Apply these relationships to other cities and in detailed agent-based model simulations

PROJECT RELEVANCE (cont.)

- Why study one-way carsharing?
  - Unique existing data set with detailed user survey responses linked to their trip origins-destinations (O-Ds)
  - Similarities to/differences from TNCs
    - Not everyone wants to ride in a TNC with a stranger driving
    - One-way carsharing may be complementary to other shared modes (e.g., public transit, TNCs, bikesharing, etc.)
    - TNC: vehicle comes to user; carsharing: user walks to vehicle
    - With automated vehicles, one-way carsharing and TNCs converge into same service
  - Builds on existing survey of users on VMT and mode shift impacts, to understand spatial factors of survey responses at very low cost to DOE
    - $1m from US DOT FHWA, car2go, City of Seattle, San Diego Assn of Governments
    - Survey conducted and analyzed by UC Berkeley
  - car2go program in San Diego had a unique all-EV fleet, which is future model for automated TNC services

MILESTONES

Date	Pillar	Milestone	Status
Sep 2017 (INL)	MDS	Compile socio-economic and transit data on 5 cities into a database	Completed
Dec 2018 (LBNL)	MDS	Develop statistical models to estimate relationship between spatial distribution of car2go impacts and characteristics in each city	In Progress
Mar 2019 (LBNL)	MDS	Use models to estimate energy and other impacts of one-way carsharing in a new city	In Progress
Sep 2019 (LBNL)	MDS	Write journal article summarizing results Use findings as inputs to LBNL BEAM model to simulate one-way carsharing in SF Bay Area	On schedule

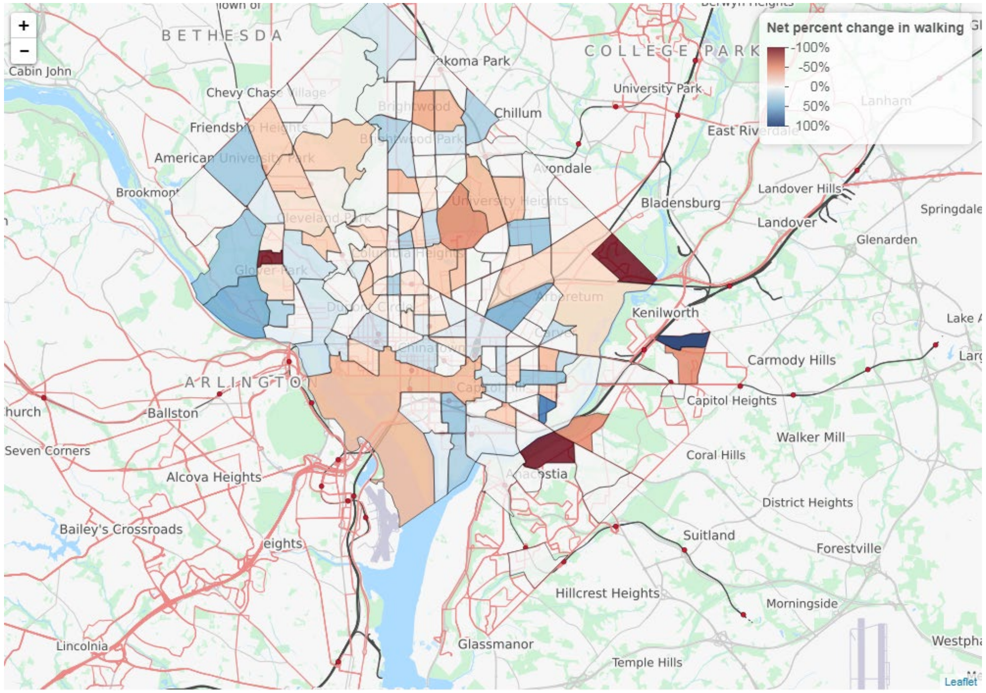
APPROACH

- Analyze the spatial distribution of 9,500 car2go survey respondents in five North American cities
  - San Diego
  - Seattle
  - Washington DC
  - Calgary
  - Vancouver
- UCB survey responses provide info on
  - Home/work location
  - Mode shift
  - Vehicle shedding
  - Vehicle suppression
  - Change in VMT
  - Vehicle activity
- Individual trip data (LBNL)
  - All car2go trips in one year (>1m trips across 5 cities)
  - Origins/destinations (O/Ds) and measured distance of each trip
  - Trips taken by survey respondents identified
- Create database of characteristics in each city (INL)
  - Census tract demographics
  - Public transit system infrastructure
  - Transit ridership data
  - Transit schedule data (GTFS)
  - Urban land use and form
- Use data visualization and regression to estimate relationships between census tract characteristics and car2go use and impacts in each city (LBNL)

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

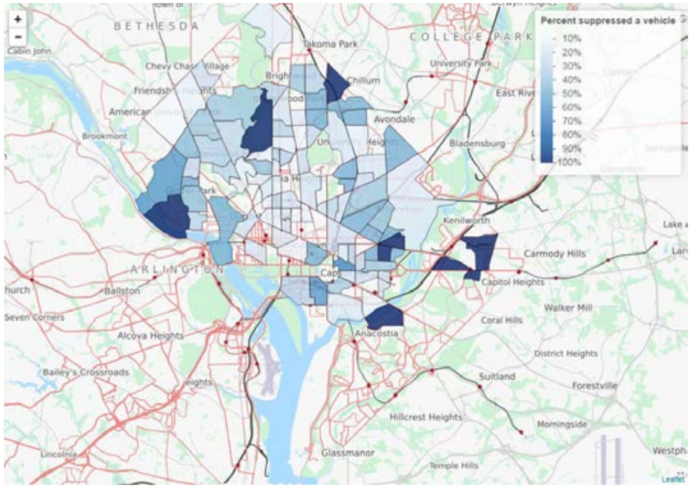
- Mapping impacts allow analysis of how urban form influences the impacts of shared mobility
- Changes in walking are mixed in Washington DC
  - –outer regions show slight increase
  - –north central areas show an overall net decline

Net Change in Walking in Washington DC due to car2go



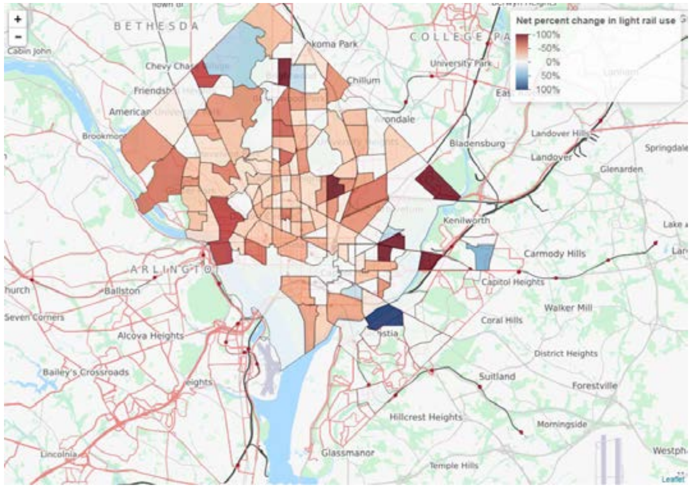
TECHNICAL ACCOMPLISHMENTS AND PROGRESS

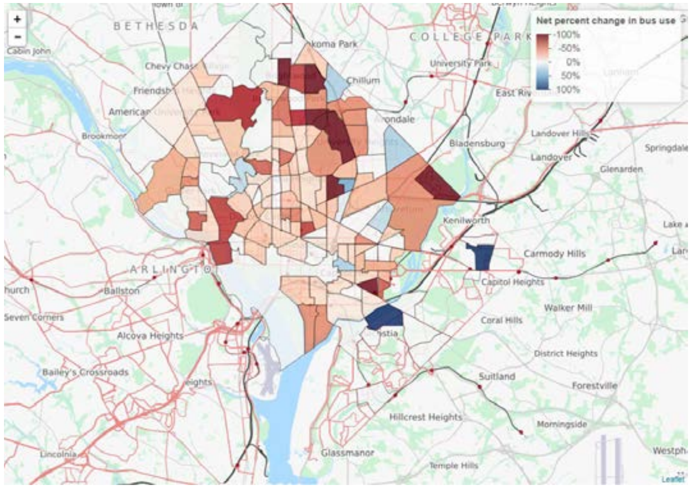
Vehicle Shedding



Vehicle Suppression

Rail Use



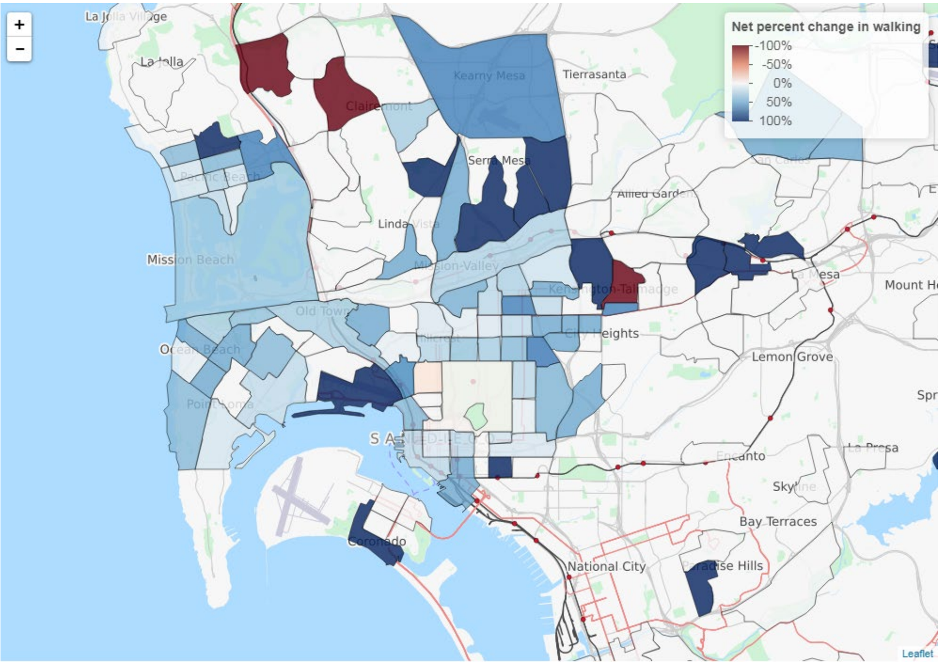


Bus Use

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

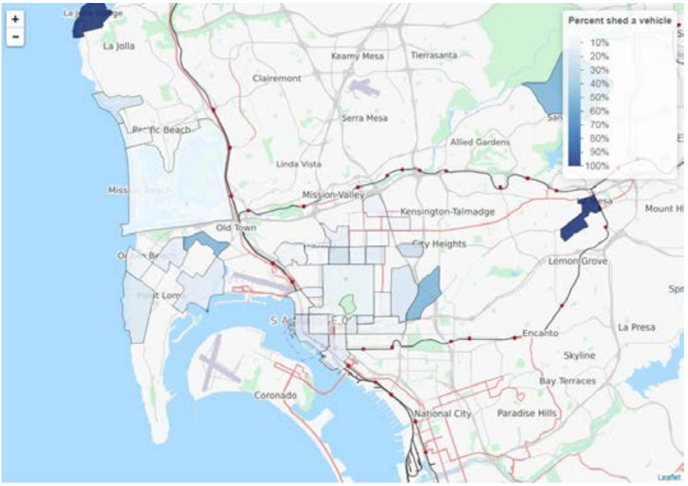
- Cities share spatial patterns for some impacts
- At the same time, more pronounced differences occur other impact
- San Diego provides one example of contrast to Washington DC
  - Walking increases broadly across the City of San Diego

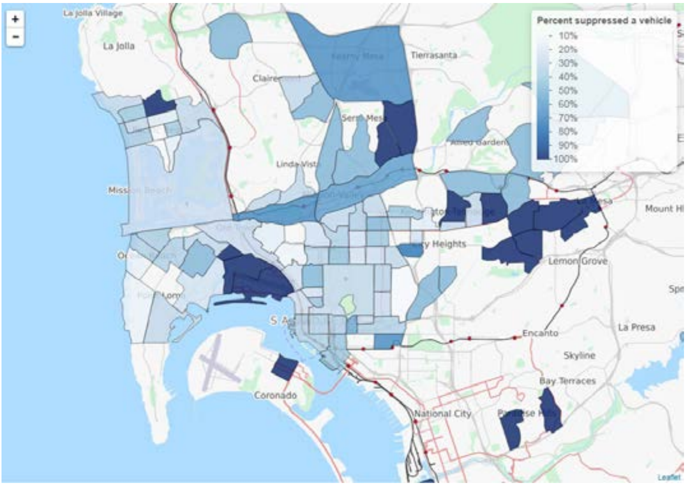
Net Change in Walking in San Diego due to car2go



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

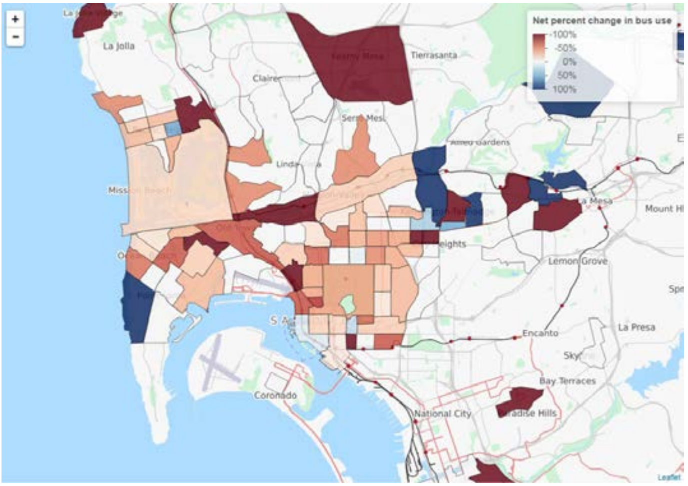
Vehicle Shedding

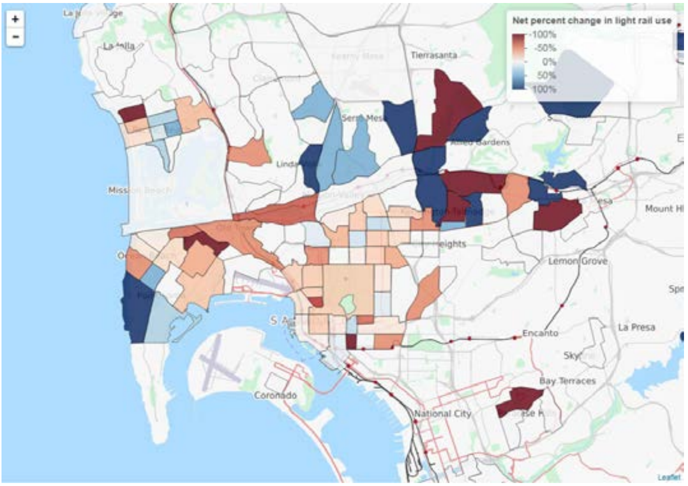




Vehicle Suppression

Bus Use

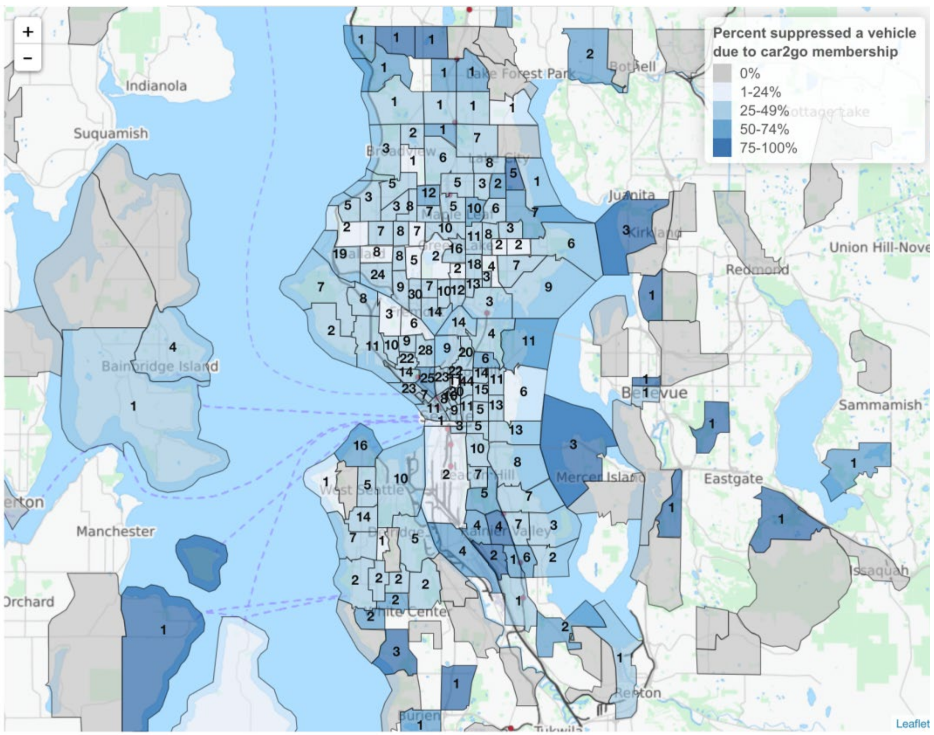




Rail Use

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Vehicle Suppression



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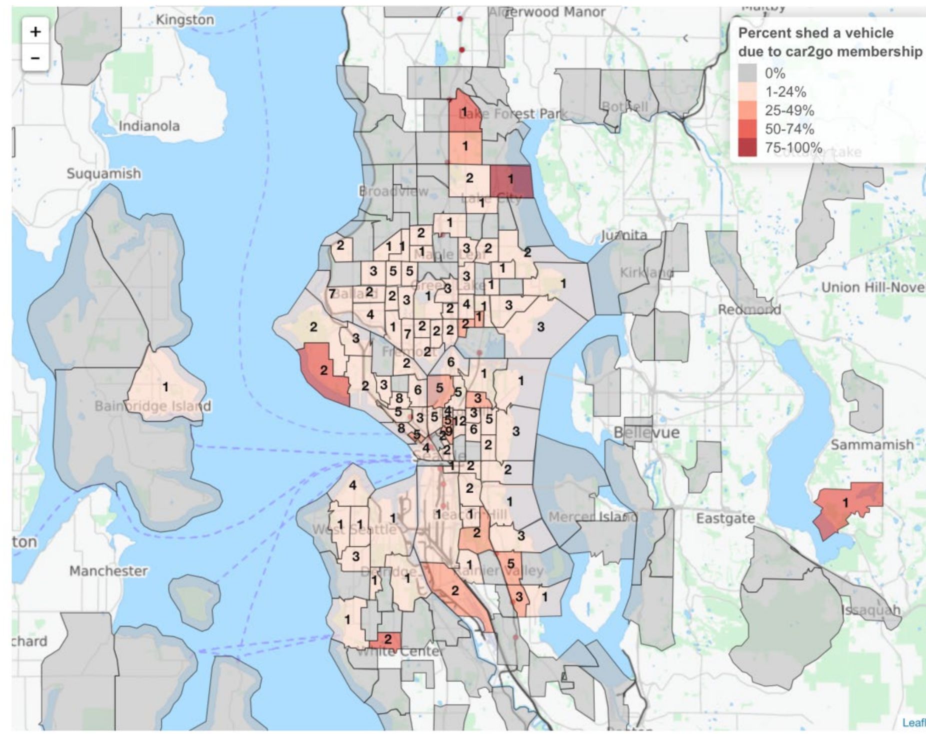

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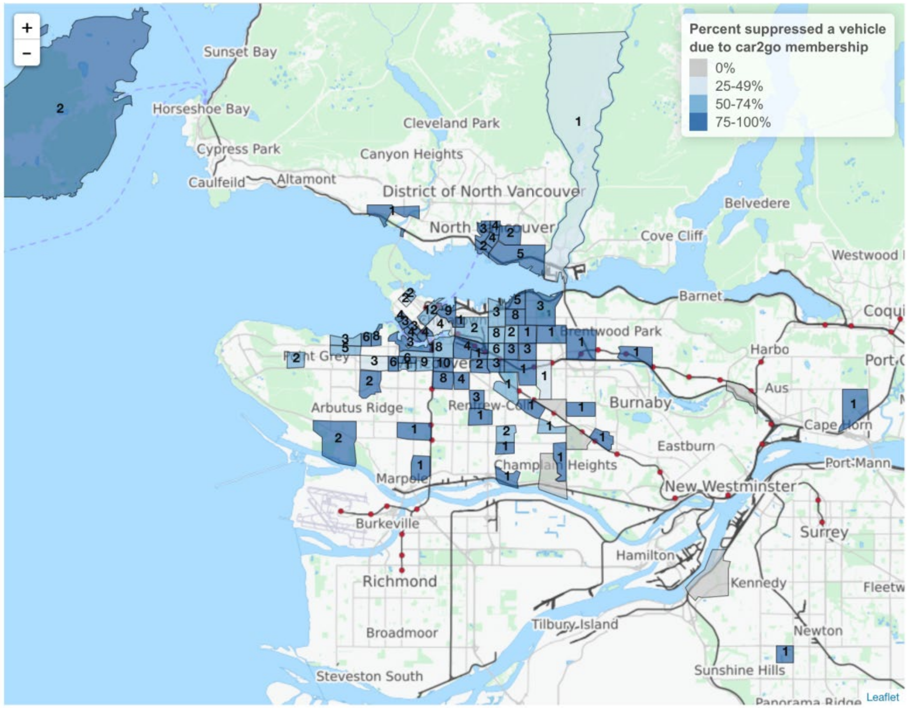

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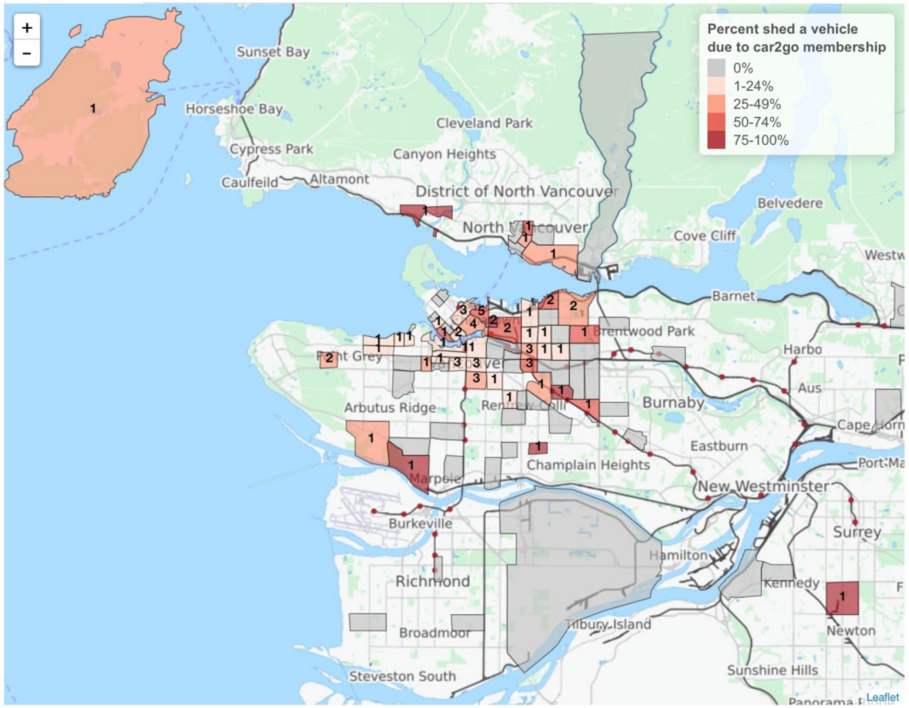
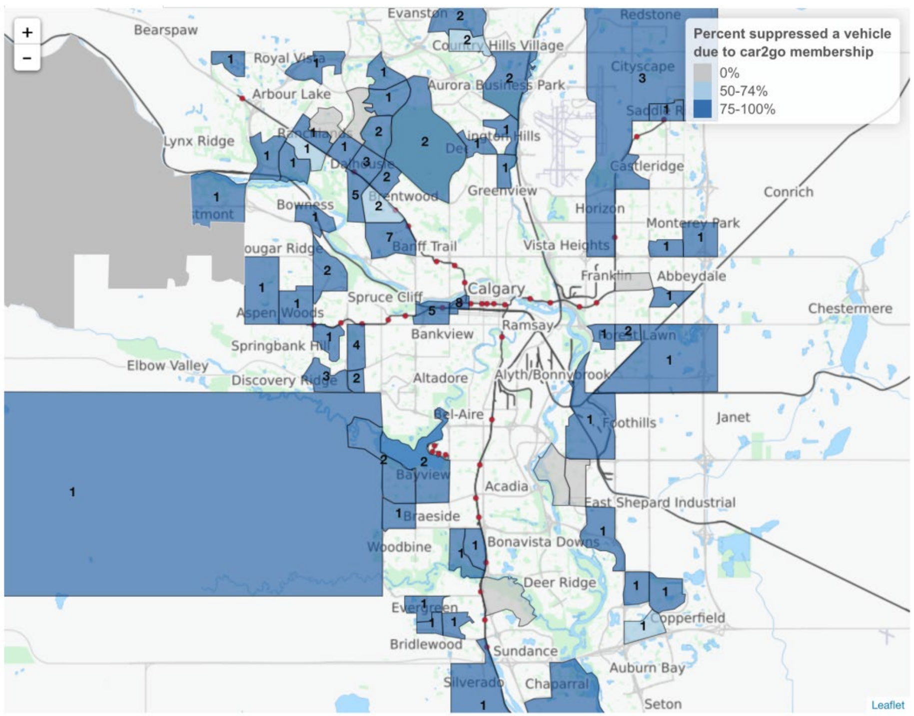
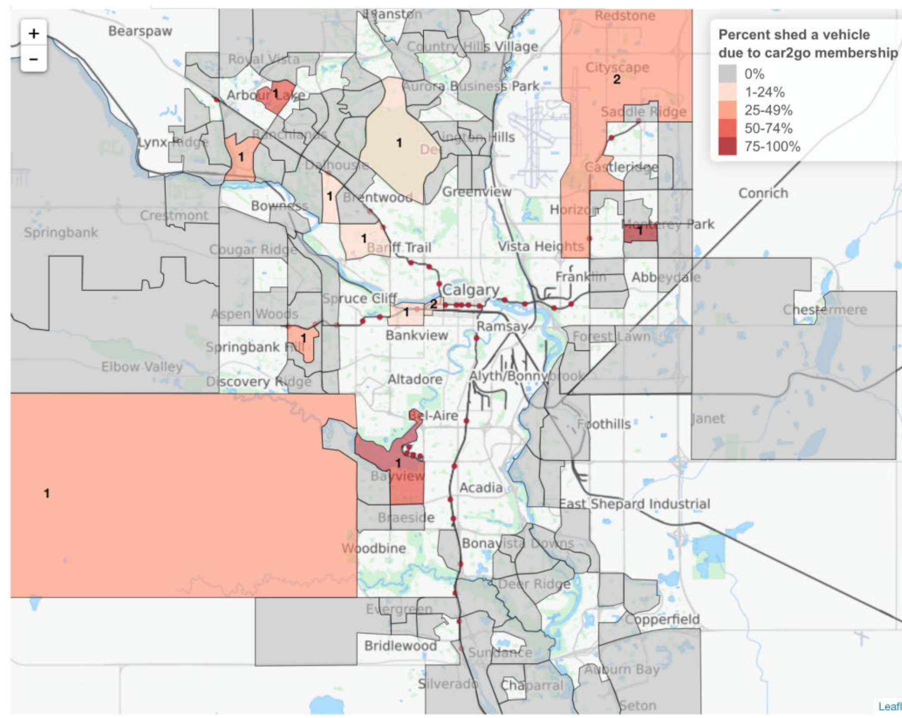


TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Vehicle Suppression



Vehicle Shedding



TECHNICAL ACCOMPLISHMENTS AND PROGRESS
Regression methods

- Developed 5 logistic regression models, each with different dependent variable
  - Vehicle shedding (getting rid of a personal vehicle)
  - Vehicle suppression (not acquiring a personal vehicle)
  - Increased/decreased use of public buses
  - Increased/decreased use of public light rail
  - Increased/decreased amount of walking
- Unit of analysis is individual survey respondent
- Over 30 independent variables were tested or applied, depending on the model
- Models developed for three US cities
- An iterative Lasso technique was applied to minimize re-prediction error using training and testing data sets

TECHNICAL ACCOMPLISHMENTS AND PROGRESS
Regression results (Vehicle Shedding Model)

	More Likely to Shed Vehicles	Less Likely to Shed Vehicles
Individuals who have…[1]	- More personal vehicles owned/leased - Household income of $15,000 to $24,999	- More commute days - Household income of $200,000 or more
Individuals who live in Census tracts with…[2]	- More household incomes of $75,000 to $99,999 - More people who use the subway to get to work - More people who travel 45 to 59 minutes to get to work	- More people who did not graduate from high school - More 6-person households - More household incomes of $25,000 to $74,999 - More people who use a vehicle to get to work
Individuals who live in areas with…[3]	- Higher employment - More zero-car households - Larger residential density - More jobs within a 45-minute transit commute	- More workers earning $1250/month or less

RESPONSES TO PREVIOUS YEAR'S REVIEWERS' COMMENTS

- Generally positive comments were received by all reviewers
- One potential weakness noted is that "the data may not accurately interpret cause and effect relationships"
  - Our intention is that the modeling provides some insights as to the cause and effect relationships of the factors that are observable in association with the impacts analyzed. This is revealed in the model that is presented. It is not seeking cause and effect relationships directly, but may provide insights into possible causes of effects that can be explored in the future.
- One reviewer noted that the findings can be applied to other types of shared mobility modes in other environments, as well as provide a better understanding of how systems perform in specific environments to support more efficient decisions on designing public transit.
  - We agree with this assessment. Our hope is to generate the data to advance such analyses for comparisons and improved understanding of impacts across the spectrum of shared mobility modes.

COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

Susan Shaheen, PhD
PI of Task for LBNL
Expert in shared mobility research both in the U.S. and internationally.

Elliot Martin, PhD
Task Lead for LBNL
Researcher in shared mobility, public transit, and transportation energy related domains

Victor Walker
PI of Task for INL
Intelligent/autonomous systems, computer science, and database design

Tom Wenzel
Berkeley Rep at LBNL
Vehicle technology, land-use patterns, travel behavior, and policy impacts on energy use and emissions.

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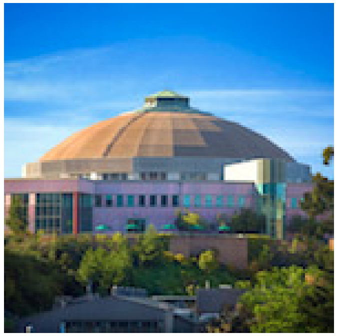
INL Idaho National Laboratory

ITS Berkeley
Institute of Transportation Studies



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RESEARCH CENTER

REMAINING CHALLENGES AND BARRIERS

- None identified

PROPOSED FUTURE RESEARCH

In FY19:

- Develop similar models for two Canadian cities
- Apply observed relationships to estimate likely potential impacts of one-way carsharing in a different city

Beyond FY19:

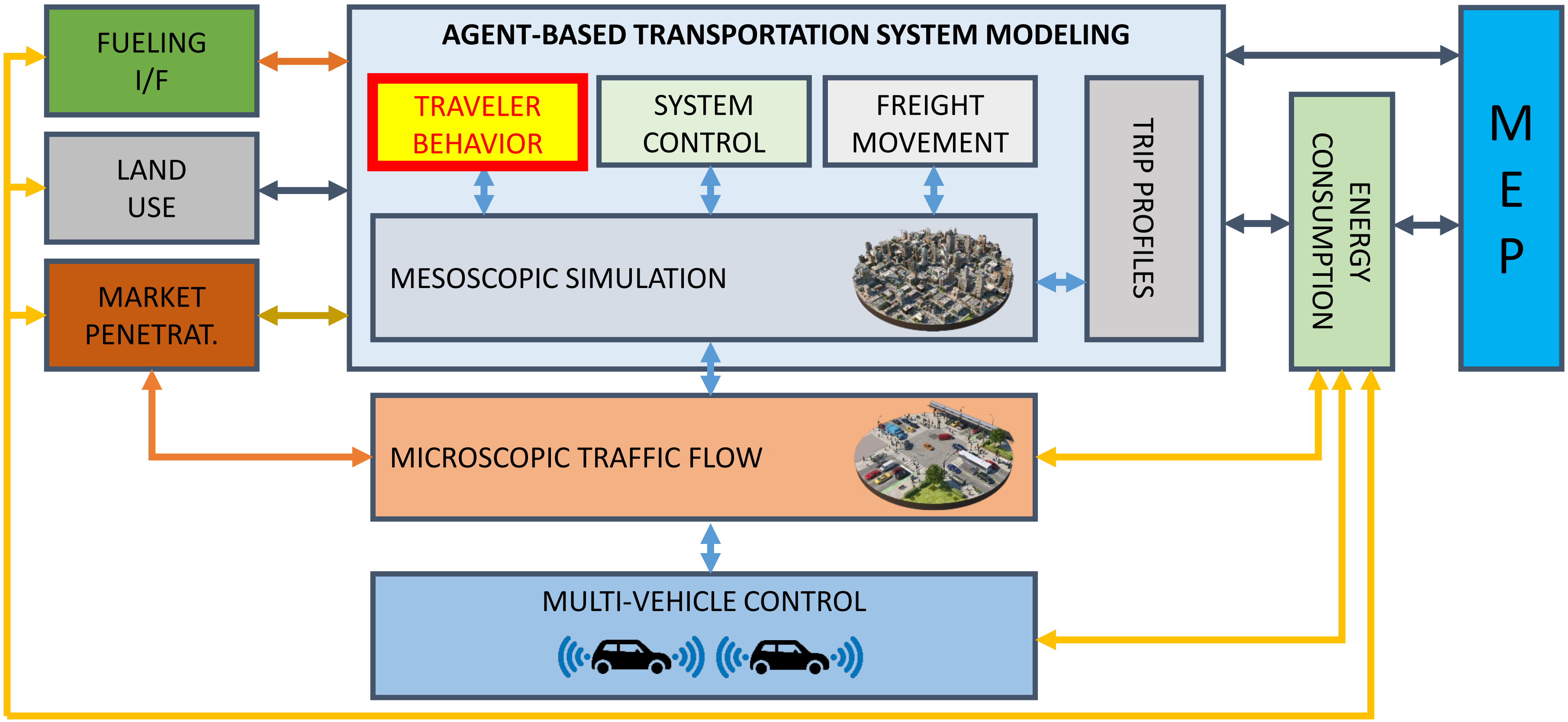
- Apply similar analysis to other shared mobility modes
  - Are the patterns of impact, and the factors associated with such impacts, similar?
- Analyze the deeper relationship between public transit energy use and ridership
  - Energy use and ridership by public transit route can provide insights where public transit is relatively more efficient
  - Develop planning tools for evaluating the efficiency of different shared mobility interventions and their interface with public transit
- Analyzes the net energy implications of micromobility systems (shared bikes, e-bikes, e-scooters)
  - Distribution of micromobility travel can generate insights about general travel demand

[Note: Any proposed future work is subject to change based on funding levels]

SUMMARY

- This project mapped impacts from one-way carsharing programs in 5 cities
- Improves our understanding of one-way carsharing impacts (changes in public transit use, active modes, and vehicle ownership) in different built environments
- The work will help evaluate the environments in which one-way carsharing and other shared mobility systems may support or undermine public transit
- The methodologies may be extended to other types of shared mobility modes, in other environments, in future work
- Better understanding of performance in specific environments can support better decisions on designing shared mobility systems to support existing public transit systems

END-TO-END MODELING WORKFLOW



QUESTIONS?

TECHNICAL BACK-UP SLIDES

CARSHARING IMPACTS VARIABLES USED IN REGRESSION MODELS

- Response ID (unique identifier)
- Bus Use (1 if they increased their bus use, 0 if they decreased their bus use)
- Light Rail Use (1 if they increased their light rail use, 0 if they decreased their light rail use)
- Walking (1 if they increased the amount they walk, 0 if they decreased the amount they walk)
- Number of Vehicles Prior to Joining Carsharing (numerical variable)
- Number of Commute Days Prior to Joining Carsharing (numerical variable)
- Gender (categorical variable)
- Age (numerical variable)
- Education (categorical variable)
- Ethnicity (categorical variable)
- Number of People in Household Aged 0-5 (numerical variable)
- Number of People in Household Aged 6-15 (numerical variable)
- Number of People in Household Aged 16-18 (numerical variable)
- Number of People in Household Aged 19-65 (numerical variable)
- Number of People in Household Aged 66 or Older (numerical variable)
- Income (categorical variable)
- Shed Vehicle (1 if they shed a vehicle, 0 if they did not shed a vehicle)
- Suppressed Vehicle (1 if they suppressed a vehicle, 0 if they did not suppress a vehicle)

LOCATION VARIABLES USED IN REGRESSION MODEL

- Education
- Unemployment Rate
- Household Type (Percent that are a Family, Percent that are Not a Family)
- Household Size
- Number of Housing Units
- Household Income
- Time they Leave for Work
- Density of Bus Stops
- Transportation Modes Used to Get to Work
- Place of Work
- Ethnicity
- Gender
- Age
- Tenure (Percent that Own their House, Percent that Rent their House)
- Total Population
- Personal Vehicles in Household
- Travel Time to Work

RELATIONSHIPS ESTIMATED BY REGRESSION MODEL
Example of Vehicle Shedding

β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}
-2.5838	0.4549	-0.0533	0.0203	-0.1350	-0.2357	-0.0782	-3.0324	-0.7090	-0.0047	0.5555

β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}	β_{19}
-1.2320	0.2339	0.8302	3.39×10^{-7}	0.1625	1.66×10^{-5}	-0.0311	0.0008	7.42×10^{-6}

β_0 is the y-intercept
β_1 is the number of vehicles prior to joining carsharing (from survey)
β_2 is the number of commute days prior to joining carsharing (from survey)
β_3 is the dummy variable representing the income bracket of “$15,000 to $24,999” (from survey)
β_4 is the dummy variable representing the income bracket of “$200,000 or more” (from survey)
β_5 is the dummy variable representing the income bracket of “Prefer not to answer” (from survey)
β_6 is the percentage of tract that did not graduate high school (from Census)
β_7 is the percentage of tract with a 6-person household (from Census)
β_8 is the percentage of tract that has a household income of $25,000 to $49,999 (from Census)
β_9 is the percentage of tract that has a household income of $50,000 to $74,999 (from Census)
β_{10} is the percentage of tract that has a household income of $75,000 to $99,999 (from Census)
β_{11} is the percentage of tract that uses a vehicle to get to work (from Census)
β_{12} is the percentage of tract that uses the subway get to work (from Census)
β_{13} is the percentage of tract that travels between 45 to 59 minutes to get to work (from Census)
β_{14} is “total employment in CBSA” (from EPA)
β_{15} is “percent of zero-car households in CBG” (from EPA)
β_{16} is not defined in the Smart Location Database (from EPA)
β_{17} is “percent of workers earning $1250/month or less (work location), 2010” (from EPA)
β_{18} is “gross residential density (HU/acre) on unprotected land” (from EPA)
β_{19} is “jobs within 45-minute transit commute, distance decay (walk network travel time, GTFS schedules), weighted” (from EPA).